Single Image Super-Resolution VIA Iterative Back Projection Based Canny Edge Detection and a Gabor Filter Prior

Rujul R Makwana, Nita D Mehta

Abstract— The Iterative back-projection (IBP) is a classical super-resolution method with low computational complexity that can be applied in real time applications. This paper presents an effective novel single image super resolution approach to recover a high resolution image from a single low resolution input image. The approach is based on an Iterative back projection (IBP) method combined with the Canny Edge Detection and Gabor Filter to recover high frequency information. This method is applied on different natural gray images and compared with different existing image super resolution approaches. Simulation results show that the proposed algorithms can more accurately enlarge the low resolution image than previous approaches. Proposed algorithm increases the MSSIM and the PSNR and decreases MSE compared to other existing algorithms and also improves visual quality of enlarged images.

Index Terms— Canny Edge Detection, Gabor Filter, IBP, Super Resolution.

I. INTRODUCTION

Super resolution is a process for obtaining one or more high-resolution image(s) from one or more low-resolution input image(s). It has a wide range of applications such as remote sensing, video communication, surveillance, consumer electronics, enlarging consumer photographs, medical imaging, computer vision, video surveillance systems et al.

A wide range of Super Resolution reconstruction algorithms have been developed in the field of image processing. In 2003, S. C. Park et al. [1] gave an excellent technical overview on the general super resolution techniques.SR reconstruction techniques can be employed in the spatial or frequency domain. Spatial domain algorithms allow more flexibility in incorporating a priori constraints , noise models, and spatially varying degradation models. A typical SR image reconstruction algorithm consists of three stages, namely, registration, interpolation and restoration. These steps can be performed independently or simultaneously depending on the approach taken. Registration refers to the estimation of the relative shifts of each LR frame with respect to a reference LR image with subpixel accuracy. Since the shifts between LR images are arbitrary, non-uniform interpolation is required to obtain a uniformly spaced HR image. Finally, image restoration is applied to the up sampled image to remove blurring and noise[2].

Very famous interpolation methods are used for initial enhancement like Nearest Neighbor (NN), Bilinear (BI) and Bicubic(BC) methods. These methods can generate smooth HR image, which are usually blurred because interpolation cannot reconstruct the high frequency component back. In [3], edge directed interpolation is proposed to preserve edge sharpness. In [4], M. Irani and S. Peleg proposed the iterative algorithms for SR reconstruction. This method uses multiple simulated LR image of similar scene to find corresponding HR image. In [5], Dai et al. uses bilateral filter with the IBP method for single LR image. An improved IBP method was given by Qin [6] in which initial value is estimated through wavelet locally adaptive algorithm rather than traditional interpolation method. In [7], Dong et al. proposed a novel non-local IBP algorithm for image enlargement which is to incorporate adaptively the non-local information into the IBP process and as a result of it the reconstruction errors can be reduced. In [8], Liang et al. proposed an improved NLIBP fast algorithm in which edge detection is conducted on the initially interpolated image. Use of non-local filter in the modifying process greatly reduces the time consumption.

In this paper, we propose the novel approach for single image super resolution using iterative back-projection method incorporated with high frequency information. We combine the IBP method with Canny Edge Detection and Gabor Filter with difference image. This IBP method can minimize the error significantly by back projecting the error iteratively. Proposed methods make use of simple bicubic interpolation to enlarge the image and processes it according to the IBP method. It back projects the error and also back-project the high frequency component using Canny Edge Detection and Gabor Filter and difference images of upsampled LR images to gather more back projecting error. This approach of SR is fast and robust to noise with edge perseveration. After multiple iterations, the blurring effect can be greatly reduced in enlarged images.

In Section II, the related IBP algorithm is reviewed. Section III presents proposed algorithms. Section IV presents Simulation results and analysis. Finally, section V concludes this work.

II. IBP ALGORITHM

Super resolution of the image is model as an inverse problem. That is the goal of super resolution is to reverse the effect of the down sampling, blurring and warping that relate the LR image to desired HR image[10]. Irani and Peleg proposed iterative back projection SR reconstruction technique [4] based on the concepts presented in [2] and [3].

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In this approach, the HR image is estimated by back projecting the difference between simulated LR images and the observed LR images. The process is repeated iteratively until some criterion is met, such as the minimization of the energy of the error, or until the maximum number of allowed iterations is reached.

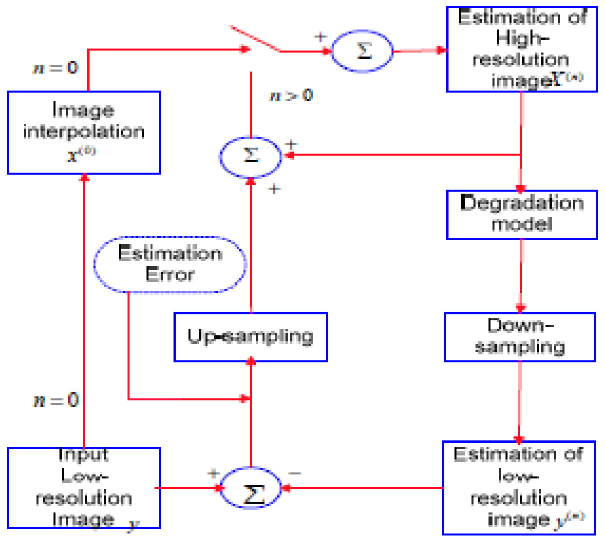


Fig. 1 Simple IBP Algorithm[10]

IBP is an efficient method that is repeated iteratively to minimize the energy of the error. The method can be used to incorporate constraints, such as smoothness or any other additional constraint which represents a desired property of the solution. In IBP approach, process starts with the input LR image. The initial HR image can be generated from the input LR image by decimating the pixels. The initial HR image is degraded and down sampled to generate the observed LR image. The simulated LR image is subtracted from the observed LR image. The HR image is estimated by high pass filter for edge projection and back projecting the error (difference) between simulated LR image and the observed LR image.

This process is repeated iteratively to minimize the energy of the error. This iterative process of SR does iterations for some predefined iterations. Block diagram of IBP algorithm is shown in fig. 1. Mathematically the SR steps according to IBP are written as:

$$X^{(n+1)} = X^{(n)} + X_e + HPF(X^{(0)}) \qquad (1)$$

Where, $X^{(n+1)}$ is estimated HR image of n+1th iteration; $X^{(n)}$ is estimated HR image of n^{th} iteration; X_e is error correction; $HPF(X^{(0)})$ is the high frequency data of the image $X^{(0)}$ that is obtained from the interpolation of initial LR image.

In IBP method, to generate the simulated LR image, the estimated HR image needs to be down sampled. Due to down-sampling procedure, sampling frequency is decreased that generates distortions in high frequency components and the aliasing problem. Therefore, the HR image obtained from High Pass filter needs to be further filtered by a Gaussian filter to eliminate the distortions from the down sampling procedure.

As a result, the updating procedure can be summarized as mathematical equation by following two steps iteratively:

1) Compute the error from LR images as

$$X_e = (y - y^{(n)}) \uparrow s \qquad (2)$$

Where, $\uparrow s$ is up-sampling; y is initial input LR image; $y^{(n)}$ is simulated LR image of n^{th} iteration; X_e is error estimation.

Estimation of the simulated LR image is given as

$$y^{(n)} = (X^{(n)} * W) \downarrow s \qquad (3)$$

Where, $\downarrow s$ is down-sampling; $y^{(n)}$ is simulated LR image of n^{th} iteration; W is degradation function; $X^{(n)}$ is estimated HR image of n^{th} iteration.

Update the HR image by back-projecting the error X_e, as equation (1).

III. PROPOSED ALGORITHM

A. Canny Edge Detection Algorithm

Though IBP method can minimize the restoration error significantly in iterative manner and gives good effect, it projected the error back without edge guidance. In proposed algorithm, extra high frequency information is added by Canny edge detection and difference error of up-sampled images from initial and simulated LR images and so that it works as edge preserving algorithm.

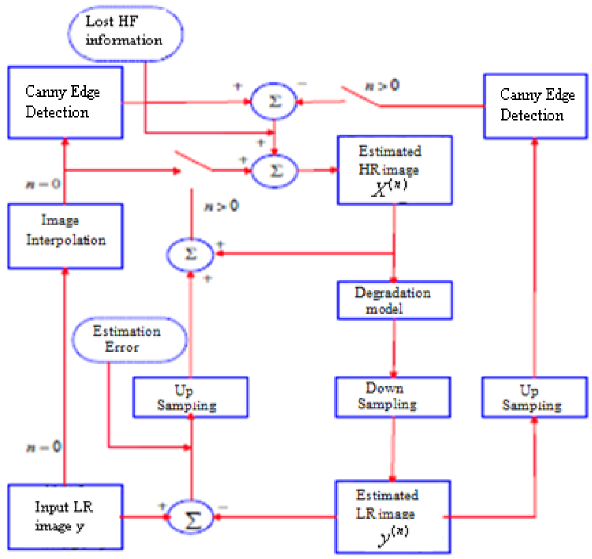


Fig. 2 Canny Edge Detection Algorithm[11]

We consider the first interpolated image $X^{(0)}$ by enlarging the original low resolution image *y* same as the IBP method. An estimated high frequency image $X^{(n)}$ is degenerated from an estimation of low resolution image *y*. So, in the iteration process, the estimated high resolution image $X^{(n)}$ will be the more similar to the original HR image $X^{(0)}$ An estimated low resolution image $y^{(n)}$ is then used to interpolate to get HR image X'. It could be predicated that X' will have more serious blurring effect than $X^{(0)}$. To overcome this effect the lost high frequency data $(X^{(0)} - X')$ is calculated and back projected to the estimated HR image to compensate the high frequency error.

The iteration process reduces the blurring effect while preserving edges. The block diagram of proposed algorithm is shown in fig.2.

B. Gabor Filter prior

Gabor filter response is successfully used in many computer vision applications like texture segmentation, face detection, iris recognition etc. In addition to IBP, a Gabor filter is a linear filter used for edge detection. Gabor Filter is used for find edges in particular direction. The Gabor filter is constructed via filter bank, consisting of filters tuned to different orientations and frequencies. The Gabor filters can also be viewed as band-pass filters whose Fourier Transform is a Gaussian shifted in frequency. The block diagram of proposed algorithm is shown in fig.3.

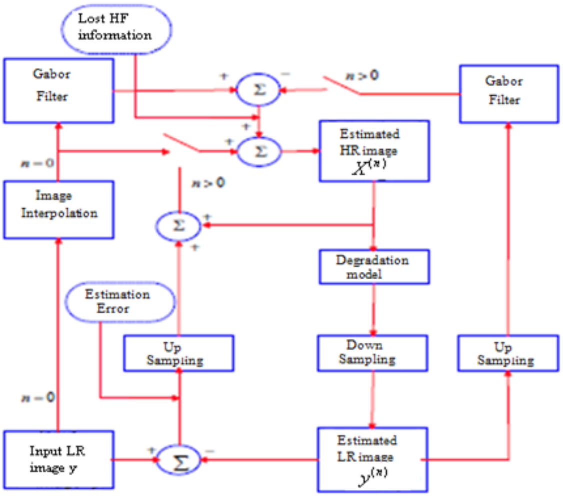


Fig. 3 Gabor Filter prior

Daugman [12] had extended the concepts of 1-D Gabor filter [13] to the two dimensional complex Gabor filter. The real and complex parts of the complex 2-D Gabor function are defined as [14]:

$$G_r(x,y)=\frac{1}{\sqrt{2\pi\sigma_x\sigma_y}}e^{-\left(\frac{x'^2}{2\sigma_x{}^2}+\frac{y'^2}{2\sigma_y{}^2}\right)}\cos(2\pi ux'+2\pi vy')$$

$$G_r(x,y)=\frac{1}{\sqrt{2\pi\sigma_x\sigma_y}}e^{-\left(\frac{x'^2}{2\sigma_x{}^2}+\frac{y'^2}{2\sigma_y{}^2}\right)}\sin(2\pi ux'+2\pi vy') \quad (4)$$

Where, $x'=x\cos\theta+y\sin\theta$
$y'=-x\sin\theta+y\cos\theta$

Here, (σ_x,σ_y) defines spread of Gaussian and *(u,v)* defines the centre frequency. The aspect ratio of the Gaussian of the Gabor is defined as σ_x/σ_y . The aspect ratio specifies the support of the Gabor function. For the aspect ratio equals to one means the support is circular. θ defines the orientation of the Gabor functions. If the value of orientation is N then N convolutions will be computed. The orientations of the respective Gabor function are equidistantly distributed between 0 to 360 degrees in increments of 360/N, starting from the value of N. The complex Gabor function in two dimensions can be represented as:

$$G(x,y,f,\sigma_x,\sigma_y,\theta)=\frac{1}{\sqrt{2\pi\sigma_x\sigma_y}}e^{-\left(\frac{x'^2}{2\sigma_x{}^2}+\frac{y'^2}{2\sigma_y{}^2}\right)}e^{j2\pi f(ux'+vy')} \quad (5)$$

According to proposed Canny Edge Detection algorithm and a Gabor Filter prior, algorithm steps for first iteration are mathematically written as :

$$X^{(1)}=X^{(0)}+X_e-X_H^{(0)} \quad (6)$$

Where, $X^{(0)}$ is initial interpolated image; X_e is error correct-ion; $X_H^{(0)}$ is high frequency estimation given by:

$$X_H^{(0)}=(X^{(0)}*HPF) \quad (7)$$

Where, $X_H^{(0)}$ is initial high frequency estimated image, HPF is canny edge detection as high pass filter.

The estimated HR image after n^{th} iterations is given by:

$$X^{(n+1)}=X^{(n)}+X_e^{(n)}+X_H^{(n)} \quad (8)$$

The estimation of the high frequency is given as

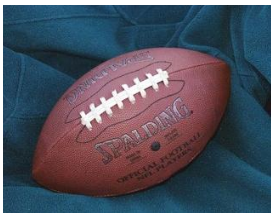
$$X_H^{(n)}=X_H^{(0)}-\{((y^{(n)})\uparrow s)*HPF\} \quad (9)$$

Where, $X_H^{(0)}$ is high frequency component of image $X^{(0)}$,this is obtained from interpolation.

So, final iteration process given in equation (9) is rewritten as

$$X^{(n+1)}=X^{(n)}+(y^{(n)}-y)\uparrow s$$
$$+\{X_H^{(0)}-\{((y^{(n)})\uparrow s)*HPF\}\} \quad (10)$$

IV. EXPERIMENT AND RESULT

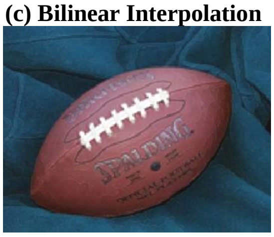


(a) Original Image

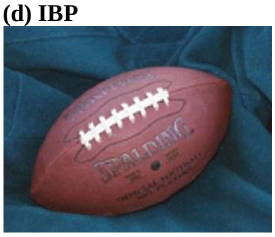
(b) NN Interpolation

(c) Bilinear Interpolation

(d) IBP



(e)Proposed Canny Edge



(f) Proposed Gabor Filter

Fig. 4. Reconstruction Result of Football image

To evaluate the SR systems effectively, this work assumes that the original HR images exist and the image quality degradation is resulted from Gaussian blurring, and such Gaussian blurring function is known. In simulations, the HR images is blurred with a 5 x 5 Gaussian blurring function of σ = 1.0and then it is down-sampled by 2 to produce LR image for experiments.LR image is up-sampled by 2 to get back HR image.

We adopt Canny edge detection algorithm to detect the strong edges in our simulation, and also more suitable results can be got by Gabor Filter Prior.

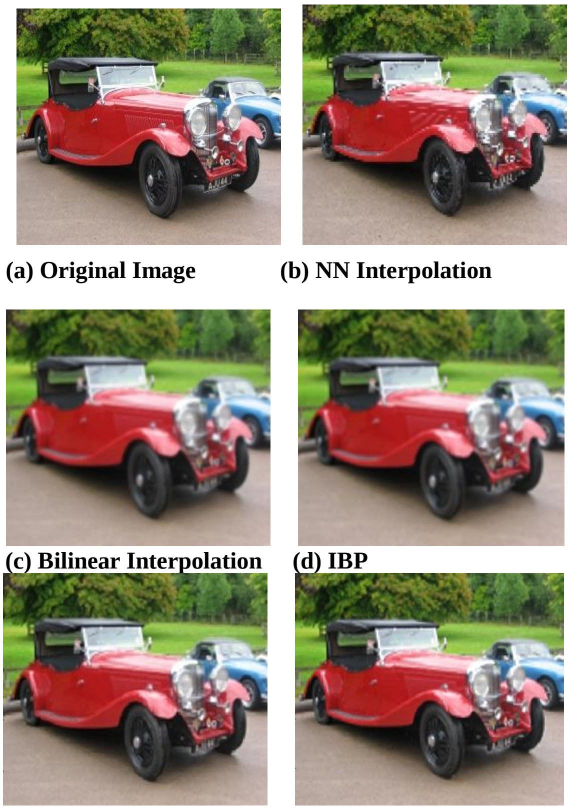
Total n = 10 iterations are taken into simulations. From Figure. 4,5,6,7,8 and table I and table II, we can find that the proposed Approach can improve the PSNR value and MSSIM value considerably in most cases.

To present the performance of the algorithm, several images of different types are tested and their results are compared with the other methods including bilinear interpolation (BI), Nearest Neighbourhood (NN), IBP. The image quality is determined based on MSSIM and PSNR evaluation. As performance criteria, Mean Structural Similarity(MSSIM) and Peak Signal to Noise Ratio (PSNR) are calculated. The mathematical equations for $M \times N$ image analysis are as given bellow.

$$MSE = \frac{\sum_i \sum_j [X(i,j) - X^{(n)}(i,j)]^2}{M \times N} \quad (11)$$

$$PSNR = 10 \log_{10}\left(\frac{255 \times 255}{MSE}\right) \quad (12)$$

Where, $X(i,j)$ is the original HR image and $X^{(n)}(i,j)$ is the estimated HR image through this algorithm.



(a) Original Image **(b) NN Interpolation**

(c) Bilinear Interpolation **(d) IBP**

(e)Proposed Canny Edge **(f) Proposed Gabor Filter**

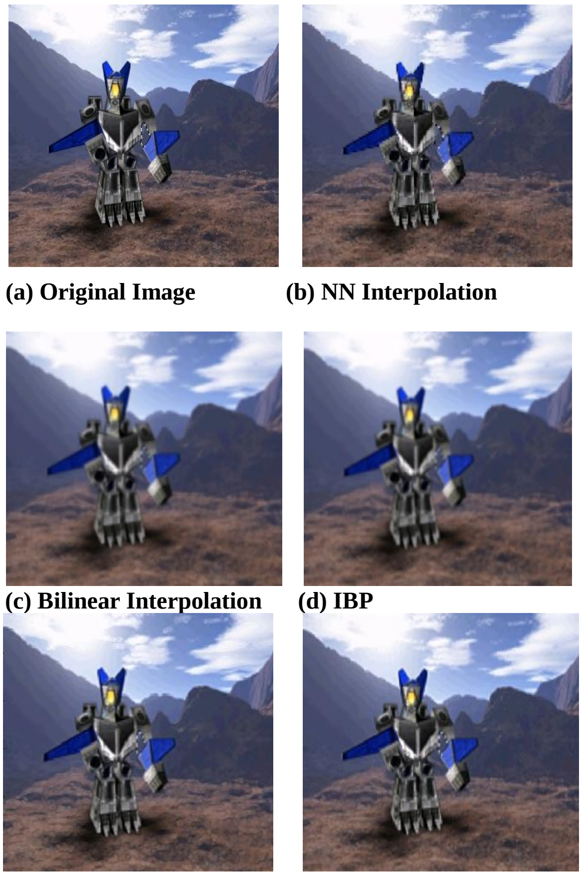
Fig. 5. Reconstruction Result of Car image

The Structural similarity(SSIM) index is defined in[15] equations:

$$SSIM(f,F) = \frac{(2\mu_f \mu_F + C_1)(2\sigma_F + C_2)}{(\mu_f^2 + \mu_F^2 + C_1)(\sigma_f^2 + \sigma_F^2 + C_2)} \quad (13)$$

$$MSSIM(f,F) = \frac{1}{G}\sum_{p=1}^{G} SSIM(f,F) \quad (14)$$

The Structural SIMilarity index between the original image and reconstructed image is given by SSIM, where μ_f and μ_F are mean intensities of original and reconstructed images, σ_f and σ_F are standard deviations of original and reconstructed images, f and F are image contents of pth local window and G is the number of local windows in the image. The value of Mean Structural SIMilarity(MSSIM) ranges between 0 and 1. A higher value means a higher structural similarity and hence better image quality.



(a) Original Image **(b) NN Interpolation**

(c) Bilinear Interpolation **(d) IBP**

(e)Proposed Canny Edge **(f) Proposed Gabor Filter**

Fig. 6. Reconstruction Result of Krogpose image

The image quality is determined based on MSSIM and PSNR evaluation. A good reconstruction algorithm generally provides low value of MSE and high value of MSSIM and PSNR. PSNR and MSSIM are obtained using various techniques and the proposed algorithms, are given in Table 1 and 2.

From Table 1 and 2, we can see that the proposed algorithm can improve PSNR and MSSIM considerably. The result obtained for different types of images with different formats(e.g PNG,TIF etc) shows improvements. The result obtained with Canny edge detection for tif and png format images shows better image quality by increases MSSIM and increases PSNR than a Gabor filter prior. The result obtained with Gabor filter for bmp, jpg and gif format images shows better image quality by increases MSSIM and increases PSNR than Canny edge detection.

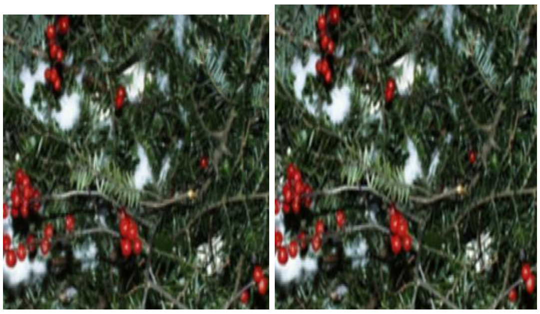
Table 1 PSNR Comparison

Tested Image	Single Frame Algorithm			Proposed Approach	
	NN	BI	IBP	Canny Edge	Gabor Filter
Football	26.91	29.38	29.22	38.19	41.72
Car	23.46	25.79	25.41	39.21	38.59
Krogpose	29.68	27.57	27.02	40.40	39.89
Greens	19.98	22.16	22.15	32.50	34.30
Lena	28.50	30.90	30.60	39.00	40.51

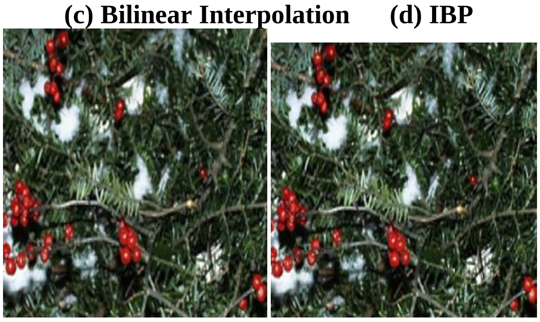
Table 2 MSSIM Comparison

Tested Image	Single Frame Algorithm			Proposed Approach	
	NN	BI	IBP	Canny Edge	Gabor Filter
Football	0.657	0.711	0.709	0.955	0.975
Car	0.715	0.760	0.759	0.975	0.982
Krogpose	0.805	0.841	0.841	0.962	0.980
Greens	0.700	0.720	0.723	0.972	0.982
Lena	0.813	0.844	0.842	0.969	0.977

(a) Original Image **(b) NN Interpolation**



(c) Bilinear Interpolation **(d) IBP**



(e)Proposed Canny Edge **(f) Proposed Gabor Filter**

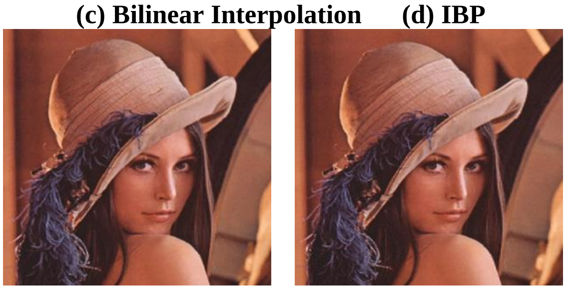
Fig. 6. Reconstruction Result of Greens image

V. CONCLUSION

The Proposed method is useful when one has to use single observed image to improve its resolution. The results obtained for different types of images with canny edge detection and Gabor filter show improvements over other approaches in terms of PSNR and MSSIM Value. In addition to IBP, high frequency data is incorporated using Canny edge detection and Gabor filter. The proposed method uses Gabor filter as a prior to analyze the image at different orientations. The quality of resultant image depends on number of orientations use in the Gabor filter. The Resolution of SR image also depends on number of iterations. As number of iterations increases quality of SR image also increases but no significant improvement is observed after few iterations. The proposed approaches perform well in both general and text images by estimating the lost information in high frequency.

(a) Original Image **(b) NN Interpolation**

(c) Bilinear Interpolation **(d) IBP**



(e)Proposed Canny Edge **(f) Proposed Gabor Filter**

Fig. 6. Reconstruction Result of Lena image

REFERENCES

1. Sung *Cheol Park, Min Kyu Park,and Moon Gi Kang* “Super Resolution:A Technical Overview,”IEEE SIGNAL PROCESSING MAGAZINE 1053-5888/03/$17.00©2003IEEE.
2. C Papathanassiou and M Petrou,” Super resolution: an overview,” 0-7803-9051-2/05/$20.00 (C) 2005 IEEE.
3. Poth Miklos, Image Interpolation Techniques, Available: www.bmf.hu/conferences/sisy2004/Poth.pdf
4. M. Irani and S. Peleg, “Improving resolution by image registration”, *CVGIP: Graphical Models and Image Processing*, vol. 53, pp. 231-239, May 1991.
5. S. Dai, M. Han, Y. Wu and Y. Gong, “Bilateral Back-Projection For Single Image Super Resolution”, *IEEE Conference on Multimedia and Expo (ICME)*, 2007, pp. 1039-1042.
6. F.Qin, “An Improved Super Resolution Reconstruction Method Based on Initial Value Estimation”, in *3rd International Congress on Image and Signal Processing (CISP)*, 2010.
7. W. Dong, L. Zhang, G. Shi and X. Wu, “Nonlocal back projection for adaptive image enlargement”, in *IEEE International Conference on Image Processing*, pp. 349-352, November 2009.

8. X. Liang and Z. Gan, "Improved Non-Local Iterative Back Projection Method for Image Super-Resolution", *Sixth International Conference on Image and Graphics (ICIG)*, 2011.
9. J. Wang, K. Liang, S, Chang and P. Chang, "Super-Resolution Image with Estimated High Frequency Compensated Algorithm", in *IEEE Conf. Communication and Information Technology*, 2009, pp. 1039-1042.
10. V. B. Patel, Chintan K. Modi, C. N. Paunwala and S. Patnaik, "Hybrid Approach for Single Image Super Resolution using ISEF and IBP", in *IEEE Conference on Communication System and Network Technology (CSNT)*, 03-05 june, 2011.
11. Milan N. Bareja and Chintan K. Modi, "A Novel Iterative Back Projection based Hybrid Approach for Single Image Super Resolution", in *National Conference on Power Systems, Embedded Systems, Power Electronics, Communication, Control and Instrumentation (PEPCCI)*, pp. 283-286, 09-11 January, 2012.
12. John Daugman: "Complete Discrete 2-D Gabor Transforms by Neural Networks for Image Analysis and Compression", IEEE Trans on Acoustics, Speech, and Signal Processing. Vol. 36. No. 7. July 1988, pp. 1169–1179.
13. D. J. Gabor, "Theory of communication", Journal of the Institute of Electrical, Engineers IEE,VOL. 93, NO. 26, pp 429-457, 1946.
14. Konstantinos G. Derpanis, "Gabor filters", York University,Version 1.3, April 23, 2007.
15. Liyakathunisa and C N Ravikumar,"A Novel Super Resolution Reconstruction of low resolution images progressively using DCT and Zonal Filter based Denoising", International Journal of Computer Science & Information Technology(IJCSIT),Vol 3,No 1,Feb 2011.